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Expert imitation in P2P markets

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Abstract

This paper investigates expert bidding imitation in peer-to-peer lending platforms. We employ data from *Renrendai.com*, which contains information of about 170,000 investors who placed almost four million bids on 111,234 loan listings from 2010 to 2018. The experts are defined as investors who either have more central roles or who spend more time or money on the network. We find that an average investor mimics the bids of expert lenders. Inactive lenders learn top investors' lending behaviour through observational learning and then, follow their actions, although they do not know the experts' identity. Finally, we show that experts rarely imitate other experts, yet they exhibit herding behaviour.

KEYWORDS

peer-to-peer lending, network analysis, expert imitation, big data, financial technology

JEL CLASSIFICATION

G11; G21; G40; G41

1 | INTRODUCTION

P2P lending platforms create an environment in which individuals can directly borrow and lend without the use of intermediaries (Serrano-Cinca, Gutiérrez-Nieto, & López-Palacios, 2015). These lending platforms offer simplified procedures and lower transaction costs as compared to traditional financial markets (Collier & Hampshire, 2010), yet they also attract investors who are not well-equipped to cope with the risks associated with lending in risky markets (Lee & Lee, 2012; Zhang & Chen, 2017). In such markets, a listing receives multiple bids and lenders (investors) generally contribute to multiple loans to diversify their risk (Zhang & Liu, 2012). Bidding information is recorded and visible to all platform users. Hence, besides borrower or loan characteristics, earlier bids of peers in the system can be taken as additional information by investors in the community when making new lending decisions. While the effects of previous bidding volume or herding behaviour have been explored in the previous literature (ial correlation and exper & Gleisner, 2009; Caglayan, Talavera, & Zhang, 2019), little is known about the impact of the composition of the crowd on lending behaviour and whether expert imitation is observed.

The literature on expert imitation is scarce. Kahle and Homer (1985) provide early evidence that expert behaviour affects individual decisions. While experts act independently, their activities affect others, prompting a followership (Aral & Walker, 2012; Hayes-Roth, Waterman, & Lenat, 1983). Kim and Viswanathan (2018) showed that experienced investors affect crowd decisions in *Appbackr*, a crowdfunding website. In P2P lending markets, the composition of the crowd could also play an important role. In particular, when investors are not well-equipped to evaluate the risks, they may choose to mimic (replicate) the actions of those who are more experienced.

In this study, we seek evidence for the presence of expert imitation in a Chinese P2P platform, *Renrendai.com*. What we propose here is related to, yet differs from, the simple herding behaviour which associates certain actions of an individual to those of the whole crowd. In this study, we question whether an individual's bidding behaviour is related to that of an expert's bids. Yet, to investigate whether ordinary investors follow experts' actions, we must come up with an approach to identify the leaders in a P2P platform. Unlike social media celebrities, experts/leaders on P2P lending platforms are not flagged or marked. We identify a P2P investment expert as an individual who has high investment intensity, defined either by the number of bids or by the amount of investments carried out by the same individual. This approach is further extended by centrality measures from network analysis in which investors (nodes) are linked (edged) if they invested in the same loan. The strength of connection can also be measured by either the amount of investment, the number of investments or a weighted measure of both.

To explore behavioural investment patterns in the crowd, we focus on *Renrendai.com*, one of the leading platforms in China (Yang & Lee, 2016), and extract data from 2010 to 2018. The dataset provides detailed socio-demographic and financial information about borrowers (e.g., income) as well as loan listings terms (e.g., interest rate or maturity). Furthermore, each loan listing contains the history of all biddings, including time span, amount of bid and investor anonymized ID. Using this information in conjunction with the centrality measures mentioned above, we identify the most active or central investors in the *Renrendai.com* universe, and call them experts.

Having defined experts, we next check whether experts' decisions influence the rest of the investors on the platform. We first implement a simple OLS model in search of a sequential correlation. This model provides the initial evidence that investors imitate experts' bidding patterns. We then include, in our empirical models, listing fixed effects and variables to control for payoff externalities; we confirm that the investment community follows the experts: Our measure of expert indicator exerts a significant and positive effect on investors' lending behaviour. As we deepen our investigation, we further find that all investors in the P2P community, including experts, herd. This observation provides evidence that herding is inherent to human nature.

This paper draws on two strands of research. First, our work is related to behavioural finance literature that discusses herding behaviour (Berger & Gleisner, 2009; Rook, 2006; Wei & Lin, 2016; Jiang, Ho, Yan, & Tan, 2018). This phenomenon is explored within P2P markets. Lee and Lee (2012) find evidence of herding behaviour in *Popfunding.com*, a Korean platform. Herzenstein, Dholakia, and Andrews (2011) study the strategic herding in *Prosper.com* while arguing that herding increases crowdfunding, but once the target is fully funded, herding diminishes. Zhang and Liu (2012) investigate the rational herding in *Prosper.com*, which contributes to the literature because the herding is considered an irrational mechanism. Similar to these studies, we observe evidence of herding behaviour. However, additionally, we provide evidence that investors observe and imitate their peers' bidding actions.

Our study is also built on the literature on expert/opinion leaders. Influential people are likely to promote the diffusion of information, innovation, social capital and behaviour in a community (Burt, 1999; Chan & Misra, 1990; Valente & Rogers, 1995; Watts & Dodd, 2007), as these people are identified as experts or opinion leaders. For instance, Trusov, Bodapati, and Bucklin (2010) provide a measure by which to detect influential people in social media based on their communication and activity and provide evidence that users can be clustered into different levels of influence in the community. Iyengar, Van den Bulte, and Valente (2011) combine a sociometric and self-reported measure to detect the influence of actors in the social network. They find that heavy social media users are more influential in new product diffusion. This study, within a P2P environment, identifies the leaders and shows that leaders impact bids of the remaining investors in the community.

We construct the paper as follows. Section 2 provides information about the data and the associated descriptive statistics. Section 3 lays out our methodology and the empirical model. Section 4 presents the results. The last section concludes the paper.

2 | DATA

2.1 | Renrendai.com

Renrendai.com, a leading P2P platform in China, was founded in October 2010; since then, it has attracted about 170,000 investors and 90,000 borrowers (Wang & Liao, 2014).[1] By the end of 2018, the platform had achieved over RMB 10 billion total investment with more than one million confirmed loans. To request a loan, a borrower initially creates a loan listing and can demand an amount ranging from 3,000 RMB to 50,000 RMB. The listing is allowed to be posted on the bidding system for up to 168 hr. In doing so, the borrower is required to submit a stylized statement describing the funding purpose, as well as information about the borrower's employment, annual income and liability.

Once the information is uploaded, the platform assigns the listing a credit rating, from AA, A, B, C, D, F to HR, where AA reflects the most recommended ranking and HR stands for "High Risk". The credit rating is based mainly on the information that the borrowers upload. Borrowers with good identification and a good credit history would be likely to receive a better credit ranking. As expected, a borrower who has defaulted, has an overdue payment, or has a criminal record would be labelled as poor-credit. Once the platform issues the credit ranking, the listing is posted on the bidding system. *Renrendai.com* provides mainly manual, automatic and hybrid bidding services. The manual bidding service allows investors to make decisions on their own. In contrast, the automatic bidding system makes decisions for the investors. The hybrid service allows investors to enjoy both automatic and manual bidding options. In this study, we focus on data from human activities only. Elimination of the automatic bidding data results in a reduction of 3% of the data.

Investors have access to listing and borrower characteristics. In general, investors bid several listings with varying characteristics so as to diversify the idiosyncratic risk associated with specific borrowers. Investors also have access to the historical bidding records on each listing. Given a listing, once the requested loan amount is filled, the loan is created and the listing is removed from the website. On average, a listing is completed within approximately 4 hr after the listing is posted; however, some other listings need a longer time for completion. The loan earnings are credited into a bank

[1]See Caglayan, Talavera, Xiong, and Zhang (2019), who also use *Renrendai.com* data for further detail on the data.

account owned by the borrower. The repayments are withdrawn automatically from the same account. However, a listing that is not funded within 7 days is identified as failed and removed from the system, while all investors who have deposited money are fully reimbursed.

2.2 | Data description

We collect data from *Renrendai.com* between the period from October 2010 to October 2018 (Platform Profile: data is updated in real time, 2020). Our data are constructed from two sources. First, we collect loan listings information about loan and borrower characteristics. Second, for each loan listing, we capture the bidding records and identify the bidder for each bidding. Hence, every specific bidding record is associated with a particular *lender ID*. We combined these two resources by utilizing the *loan ID* and generated a sample containing more than 16 million observations. For a particular *loan ID*, its loan characteristics, including annual interest rate, credit ranking, requested loan amount, listing time, maturity and duration, are recorded. The platform provides information about the borrower characteristics, including *borrower ID*, monthly income, borrower age, employment situation, residence location, educational level, immovable property ownership and credit history on the platform. When we turn to the investors' view, we have *lender ID*, bid amount on all lists and bidding time on each bid. Finally, for each loan listing, we construct a dummy variable to depict hourly human or hybrid bidding. Also, a pseudo panel on active bidders is constructed to investigate all active bidders' activities.

Table 1 shows the basic statistics on lenders. Our dataset records both bidding and borrowing information on 432,882 observations based on 3,947,996 bids on 111,234 listings. The average number of hourly bids is 6.44, with a standard deviation of 19.03. The wide variation of the bidding frequency may be associated with investors' daily routine, as investors may be more active at certain times of the day. In contrast, we observe that the average hourly number of bids attributable to experts is 1.88, with

TABLE 1 Descriptive statistics

	Mean	Std	p25	p50	p75
	(1)	(2)	(3)	(4)	(5)
Hourly Total Bids	6.44	19.03	0.00	0.00	5.00
Hourly Total Experts Bids	1.88	4.98	0.00	0.00	1.00
Hourly Total Non-Experts Bids	4.56	15.54	0.00	0.00	3.00
Hourly Bid Amount	9,368.00	23,609.70	0.00	0.00	3,500.00
Hourly Experts Amount	3,511.97	11,615.26	0.00	0.00	400.00
Hourly Non-Experts Amount	5,856.03	16,213.16	0.00	0.00	1,750.00
Hourly Experts Amount Percent	0.39	0.32	0.10	0.32	0.64
Log Bidders	5.06	2.03	3.64	4.88	5.77
Percent Needed	63.46	37.60	31.67	81.67	95.00
Obs.	432,882				

Notes: This table shows the mean (1), standard deviation (2) and quartiles (3)-(5) of the following variables. *Hourly Total Bids* represents the hourly total number of bids from lenders for a loan request. *Hourly Total Experts Bids* represents the hourly total number of bids from experts for a loan request. *Hourly Total Non-Experts Bids* represents the hourly total number of bids from non-experts for a loan request. *Hourly Bid Amount* represents the hourly bid amount a listing receives. *Hourly Experts Amount* represents the hourly bid amount a listing receives from experts. *Hourly Non-Experts Amount* represents the hourly bid amount a listing receives from non-experts. *Hourly Experts Amount Percent* represents the percentage of the bid amount a listing receives attributed to experts. *Log Bidders* represents the logarithm of number of bidders. *Percent Needed (%)* represents the percentage of the amount requested that is left unfunded.

TABLE 2 Descriptive statistics for loan characteristics

	Mean (1)	Std (2)	p25 (3)	p50 (4)	p75 (5)
Loan Amount	49,142.76	43,465.87	15,000.00	41,100.00	73,700.00
Interest Rate (%)	12.29	2.61	10.80	12.00	13.00
Maturity (Months)	21.79	12.29	12.00	20.00	36.00
Credit Risky (1 = yes)	0.22	0.41	0.00	0.00	0.00
Debt-to-Income Ratio	0.28	0.36	0.11	0.19	0.35
Monthly Income	4.37	1.28	3.00	4.00	5.00
High Education	0.67	0.47	0.00	1.00	1.00
Time on Market	4.22	17.12	0.00	0.00	0.00
Obs.	111,234				

Notes: This table shows the mean (1), standard deviation (2) and quartiles (3)-(5) of the following variables. *Loan Amount* represents the total amount of the loan received. *Interest Rate (%)* represents the annual percentage rate on the loan. *Maturity* represents the current loan duration in months. *Credit Risky (1 = yes)* means that the listing's credit grade is E or below, that is, E, F and HR, else = 0. *Debt-to-Income Ratio* represents the ratio of the borrower's monthly debt divided by gross income before the borrower applies for loans. *Monthly Income* represents the monthly income (measured by 1,000) for every borrower. *High Education* represents that the borrower holds a certificate that is above or equal to college level. *Time on Market* represents the time duration term that a listing is posted on the platform before it is full.

a standard deviation of 4.98. Furthermore, the average hourly total bid amount on the platform is 9,368 and the average expert contribution to the platform is 3,511, indicating that 37% of the investments are made by the experts. These features suggest that experts invest much more actively than do the rest, and that their investment pattern is more stable than that of the average investors, as the standard deviation associated with expert behaviour is lower.

Table 2 displays the basic descriptive statistics for all 111,234 listings in our dataset. The amount of the loan that a borrower can receive varies from 3,000 RMB to 500,000 RMB with an average of 49,142 RMB. The average interest rate is about 12.29% with a standard deviation of 2.61%. The average maturity is approximately 22 months. The platform labels 22% of the loan applications as high-risk listings. Borrowers' average debt to income ratio (DTI) is about 28%. Although DTI could be very high for some of the applicants, some borrowers do not have any outstanding debt; therefore, the DTI for such applicants is calculated as 0. Having no outstanding debt gives confidence to borrowers, as lenders in China tend to prefer funding applicants who have no or little debt. Generally, a listing reaches the requested amount within approximately 4 hr, with a standard deviation of 17 hr. A high standard deviation on completion rates implies that some listings are very popular and are completed very fast, though other listings take longer to fill, if at all. In the 1st hour, a listing receives 23 bids on average. This high average suggests that investors are eager to bid on listings, or perhaps new listings do not arrive as quickly, which causes investors to race to place a bid. This makes sense, as most of the bidders are small investors and the savings rates from banks are very low.

3 | METHODOLOGY

3.1 | Expert definitions

Our proxies of expert lenders are based on the count measure as well as network centrality measures. To implement the count measure, we employ two approaches. Using a 4-month rolling window, we calculate (a) the total amount of investment during the first 3 months (we call this period the learning interval) and (b) the number of investments for each investor.[2] Then, we identify the top 15% of the investors within each proxy and generate two separate measures to identify *experts*. Count measure is straightforward and computationally light, which provides a simple means to directly record the investment experience of members in the P2P community. However, "count" measures could not properly reflect the linkages among investors. For instance, when an investor provides funds to a loan that has a potential of 100 bidders (including this investor), the investor's action is visible to 99 investors in the community. In contrast, an investment decision on a listing that has the potential for only 10 investors to bid would be seen by only nine bidders. Practically, imitation emerges from observational learning and observational learning requires a visible signal. If the signal is not observed by as many investors as possible, the influence of expert behaviour on the community will be limited. Hence, count measures could be a good first-choice approach, but they would not capture the extent to which an investor influences other investors in the same community.

To study how signal transmissions can affect the behaviour of investors, we next apply network centrality measures. Centrality allows us to investigate the importance or influence of prominent actors in a network (Barrat, Barthélemy, & Vespignani, 2004). A network contains nodes (actors) that are associated by links (ties or edges) (Otte & Rousseau, 2002). Nodes refer to individuals who have connections to other individuals; a tie represents a unique connection between two nodes (Menichetti, Remondini, Panzarasa, Mondragón, & Bianconi, 2014). In this context, the P2P community is similar to a social network that embodies a substantial amount of information. In fact, investors in P2P communities are connected by the bidding signals dispatched by the investors who bid on various listings at a time.

Using *Renrendai* data, we construct a network on a monthly basis in which investors connect with others by observing and learning peers' behaviour. In particular, we construct connections between every individual *lender ID* who invests in the same *loan ID*; the connection is weighted by the bid amount and the bid amount is the signal that the particular *lender ID* dispatches to the other *lender ID*. Given the connections and investors, we generate an edge list that records the signal (bid information), resource, target and strength (*bid amount*). Then, we compute a degree of centrality to identify the most influential actors (investors) (Bonacich, 2007). Different measures capture the influence of actors in a network. Degree centrality, betweenness centrality and closeness centrality are the most common choices (Bonacich, 2007). As the most basic centrality measure, degree centrality captures the number of ties to a given point, which is defined as the number of links that a node has to other nodes (Opsahl, Agneessens, & Skvoretz, 2010). Betweenness centrality captures how many times a particular node serves as a bridge on the shortest path between two other nodes (Newman, 2005). Closeness centrality captures how many ties (steps) of the shortest path are required for a specific node to connect with every other point in the network (Borgatti, 1995). In this study, we estimate degree centrality to measure the number of ties, that is, connections, of a particular agent. This indicator reflects the extent to which an actor is important or central to a network (Herrero-Lopez, 2009). Ignoring the direction, degree centrality simply counts the number of ties for every actor, $C_D(k) = \sum_j^N X_{kj}$, where k is the focal node, j is all other nodes, N is the total number of nodes and x is the adjacency matrix.

As defined above, the degree centrality measure considers only the number of connections that an agent holds. However, in weighted networks, each connection is associated with a weight that represents the strength of the connection (Opsahl et al., 2010). To extend the degree centrality measure, Newman (2005) and Barrat et al. (2004) introduced the weighted degree, which summarizes

[2]We have conducted two extra checks by allowing the rolling windows to be either 3 or 5 months; we received quantitatively similar results. The results from these exercises are available from the authors upon request.

the weights of all connections. More specifically, $C_D^w(k) = \sum_j^N W_{kj}$, where W is the weighted matrix, in which if actor k connects with j, the associated element of the weight matrix, w_{kj}, represents the strength of the connection.

The original degree and weighted degree reflect the number of connections and the strength of the connections, respectively. To combine the number and the strength, Opsahl et al. (2010) introduced a balancing parameter, α, to their proposed measure, $C_D^{w\alpha}(k) = C_D(k)^{\alpha} C_D^w(k)^{(1-\alpha)}$. For our purposes, we weight the P2P network by the investment amount and we extend the degree by the sum of the weight with which we summarize the bid amount. We calculate the degree centrality by number of ties $C_D(k)$ by summarizing the total number of connections that an investor has in relation to other investors. Also, we compute the degree by the weight $C_D^w(k)$, which belongs to a *lender ID,* by summarizing the *total bid amount* that the *lender ID* dispatches to all target lenders. The degree measures the result in two rankings, which represent the connection number and the connection strength. We employ both of these two rankings and identify, as experts, the top 15% of investors in the ranking.

Unlike a simple count measure, centrality measures reflect how the information is transmitted in a community. In *Renrendai.com*, the historical bidding records are the only visible resource for investors to observe and learn from while the listing is active on the website. This information source disappears once the listing is completed and removed from the platform. Of course, past records are open to all lenders, but if we consider that the signals pass throughout a network, the lenders who invest in the same loan listing are most likely to observe and learn when the listing is actively receiving funds from the public. In a P2P platform, *bid amount* and *bid number* are the two visible resources. By taking both the number of connections and the strength of connections into account, we calculate a balanced degree of centrality. Assuming that the degree and the strength are equally important, we calculate the balanced degree centrality measure $C_D^{w\alpha}(k)$ for each *lender ID*. The balanced degree centrality provides our additional ranking from which we select, as the experts, the top 15% of investors with the highest balanced degree.[3] Using these centrality measures, we generate a dummy *Expert* to flag the expert investors in the P2P investor community.

3.2 | Empirical model

To examine the claim that expert lending behaviour influences the remaining members in the investment community, we focus on the role of the cumulative historical biddings in the previous hours on investors' current bidding decisions. While doing so, we split the previous bidding information into two groups: bids received from experts and bids received from non-experts. We are interested in investors' behaviour for a specific listing after these investors have observed the number of expert bids as well as the total amount that experts invested in the previous hour. We generate cumulative hourly bidding data for each listing, from the time a listing is posted until the listing fills up or expires.

Our first approach is based on a simple OLS model and takes the following specification:

$$\begin{aligned} Hour\,Bid\,Amount_{it} = {} & \alpha_1 Expert\,Amount\,Percent_{i,t-1} + \alpha_2 Total\,Bid\,Amount_{i,t-1} \\ & + \alpha_3 Total\,Bids_{i,t-1} + X_{it}\beta_1 + Z_i\beta_2 + e_{it} \end{aligned} \tag{1}$$

[3]We have experimented with thresholds of 10% and 20% to define experts and received quantitatively similar results. Results are available from the authors upon request.

where *Hour Bid Amountit* is the funding amount that loan i has received at time $t = 1, 2, \ldots, 60$.[4] Although *Renrendai.com* allows every loan listing to be posted on the system for up to 7 days (168 hr), we keep data on loan listings up to $T = 60$ hr because the average completion time on the platform is around 4 hr. We also observe that listings that are not funded at $T = 60$ hr rarely receive full funding by the end of 168 hr, or 7 days. Also, as noted earlier, $Hour\ Bid\ Amount_{it}$ does include investments from those who join the community in the middle of a rolling window.

The OLS specification (1) allows us to check whether investors are affected by experts in the community. The key variables of interest, $Expert\ Amount\ Percent_{i,t-1}$ and $Hour\ Bid\ Amount_{i,t-1}$, gauge lagged cumulative funding from experts and collective investors, respectively. In particular, $Expert\ Amount\ Percent_{i,t-1}$ represents the percentage of the cumulative amount which is attributed to experts in a listing i by the end of hour t-1.[5]

The model employs vectors X_{it} and Z_i to measure the time varying and time invariant. For vector X_{it}, $\%Needed_{i,t-1}$ presents the percentage of the requested amount by loan i which is left unfunded by the end of hour t-1. To capture the effect of the bidding time throughout a day, we include *Hour of Day*, H_{it-1} and *Day of Week*, D_{it-1}, as time fixed effects. Vector Z_i contains the time invariant loan characteristics, including *Requested-Amount, Maturity, Credit Risk, Debt-to-Income-Ratio* and *Property-Ownership Dummy*. The *Start Day* is also included in Z_i to measure the opening date for the loan listing. Because our data incorporates information from both manual bidding and manual-auto-hybrid bidding services, we introduced lagged *Percent Auto Bidding* in our model to control for the effect of machine bidding for the subscribed investors. The e_{it} denotes the error term.

Model (1) could not be used to capture the presence of observational learning and imitation. This is because sequential correlation could materialize as a result of unobserved heterogeneity across loan listings. To control for unobserved heterogeneity in the data, we modify our model and introduce listing fixed effects, μ_i. The model now takes the following form:

$$\begin{aligned} Hour\,Bid\,Amount_{it} &= \alpha_1 Expert\,Amount\,Percent_{i,t-1} + \alpha_2 Total\,Bid\,Amount_{i,t-1} \\ &\quad + \alpha_3 Total\,Bids_{it-1} + X_{it}\beta_1 + \mu_i + v_{it} \end{aligned} \tag{2}$$

Both models (1) and (2) are estimated using five definitions of “expert”.

In addition to “following the crowd”, investors’ decisions could be driven by payoff externalities (Arieli, 2017). On *Renrendai.com*, investors take the opportunity cost that investing in a listing that may fail to complete. Although the contribution is fully refunded if the listing fails, investors still waste their time and potential opportunity. Hence, investment into nearly completed listings has several advantages. This fact may further boost the completion speed and enhance the impacts of expert imitation and herding.

To capture the payoff externalities, we interact the *Lag Percentage Need*, the percentage remains unfunded to measure the opportunity cost, with the *Lag Total Bid Amount*. The augmented model is shown below:

$$\begin{aligned} Hour\,Bid\,Amount_{it} &= \alpha_1 Expert\,Amount\,Percent_{i,t-1} + \alpha_2 Total\,Bid\,Amount_{i,t-1} + \alpha_3 Total\,Bids_{i,t-1} \\ &\quad + X_{it}\beta_1 + Z_i\beta_2 + \alpha_4 Total\,Bid\,Amount_{it-1} \times Lag\,Percentage\,Need + e_{it} \end{aligned} \tag{3}$$

[4]We have also experimented with a normalization of all variables except percentages by loan size. Results are similar to those reported in the paper and are available from the authors upon request.

[5]The results are qualitatively similar if we replace the percentage of the cumulative amount of bids made by experts with the percentage of cumulative number of bids made by experts.

4 | RESULTS

Table 3 presents the results for the presence of sequential correlation using all five expert proxies that we described above. These regressions control for loan- and borrower-specific characteristics. Next, Table 4 presents the results for expert imitation after we introduce both the hour of day and the listing fixed effects into the model. Table 5 presents the results for expert imitation among different categories of investors after we categorize investors into different groups based on experience.

4.1 | Sequential correlation

Using the expert identifiers from both count measures and centrality measures, we examine for sequential correlation in Table 3. We include *Expert Amount Percent,* the percentage of the cumulative amount which is attributed to expert; *Lag Total Bid Amount* refers to the funding amount that the listing receives. Columns 1–2 show the results based on the expert definition stemming from the count measure by amount, or by the number of bids. The last three columns report the results based on expert lists stemming from degree centrality by weight, the number of ties and the balanced degree centrality measure.

To detect expert imitation, we inspect the coefficient associated with *Expert Amount Percent*. The positive significant *Lag Expert Amount Percent* coefficient suggests that the expert decisions have a significant influence on investors in the *Renrendai* community: A listing receiving more past contributions from experts does attract more subsequent funding. Precisely, if *Lag Expert Amount Percent* increases by 50 percentage points, we would expect to observe an approximately 6 to 8 percent increase in the funding that a listing receives in the next hour. In other words, when investors explore the historical biddings, if there are more amount attributes to experts instead of average non-experts, they would provide more contributions to this listing. Overall, the more experts who appear on the historical bidding record, the more appealing the listing becomes to the observant investors.

Apart from expert imitation, we also observe evidence of herding. The coefficient of *Lag Total Bid Amount* is statistically significant and positive as well, which suggests that the more lenders contribute, the more investors would follow. A similar finding was reported by Zhang and Liu (2012). Furthermore, we find that *Lag Total Bids* takes a positive coefficient in all the columns, suggesting that the earlier the bids appear in a listing, the more future investors will provide funding. This finding also supports herding behaviour, as investors, while making decisions, observe both the bids list and the amount of all bids.

When we turn to the remaining independent variables in the model, we first find that the *Automatic Bidding Percent* negatively affects the hourly bid amount, which suggests that the automatic bidding system discourages the investment intent on listings. This is interesting, as the primary function of the automatic bidding service is to ease investors' decision-making problem and therefore, increase the overall amount invested in a listing. *Lag Percentage Needed* has a positive effect, which indicates that when a listing approaches completion, investors' interest in this listing declines. As a result, it takes a slightly longer time to fill the listing. We find that *Amount Requested* has a positive effect on the total bid, which indicates that a listing that asks for a larger amount can attract the attention of investors. *Log (number of) Bidders* has a positive impact on the amount of the bid. This is meaningful because as the number of bidders increases, so does the amount bid on a listing.

Our results show that several borrower and listing characteristics also affect the lenders' decision. *Interest Rate* takes a positive coefficient, reflecting that investors are attracted by high returns. *Log (Monthly) Income* has a positive coefficient, suggesting that investors prefer to fund applicants with

TABLE 3 Sequential correlation and expert imitation

	Count amount	Count bids	Degree amount	Degree bids	Balanced degree
	(1)	(2)	(3)	(4)	(5)
Lag Expert Amount Percent	0.122***	0.133***	0.127***	0.169***	0.152***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Lag Total Bid Amount	0.313***	0.316***	0.313***	0.318***	0.318***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Lag Total Bids	0.011***	0.011***	0.011***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lag Percentage Needed (%)	0.009***	0.009***	0.009***	0.008***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag Percent Automatic Bidding	−0.801***	−0.792***	−0.795***	−0.824***	−0.812***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Amount Requested	0.163***	0.162***	0.162***	0.158***	0.152***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Interest Rate (%)	0.013***	0.012***	0.013***	0.013***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Maturity	−0.018***	−0.018***	−0.018***	−0.018***	−0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Monthly income	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
High Education	0.012**	0.014**	0.015***	0.011**	0.013**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Credit Risky	−0.105***	−0.102***	−0.102***	−0.103***	−0.105***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Debt-to-Income Ratio	−0.004	−0.001	−0.002	0.002	−0.012
	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)
Log Bidders	1.231***	1.231***	1.232***	1.231***	1.230***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Lag Total Amount × Lag Percentage Needed (%)	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	432,882	432,882	432,882	432,882	432,882
R^2	0.849	0.849	0.848	0.849	0.849

Notes: This table shows the sequential correlation of the following variables based on (1) Count Amount Method, (2) Count Bids Method, (3) Degree Amount Method, (4) Degree Bids Method and (5) Balanced Degree Method. The dependent variable of all five clusters is *Log Hour Bid Amount. Lag Expert Amount Percent* represents the percentage of the total amount of the loan received from experts at time *t*-1. *Lag Total Bid Amount* shows the total amount of funding from collective investors at *t*-1. *Lag Total Bids* represents the total number of bids at *t*-1. *Lag Percentage Needed (%)* represents the percentage of the amount requested that is unfunded at *t*-1. *Amount Requested* represents the requested loan amount. *Interest Rate (%)* represents the annual interest rate of the loan. *Maturity* represents the loan duration in months. *Monthly Income* represents the monthly income of the particular borrower. *High Education (1 = yes)* represents whether the borrower holds a high education certificate. *Credit Risky (1 = yes)* represents the listing's credit grade, that is, E, F or HR, else = 0. *Debt-to-Income Ratio* represents the ratio of the borrower's monthly debt divided by gross income before they apply for loans. *Log Bidders* represents the logarithm of bidder numbers. *Lag Percent Automatic Bidding* shows the percentage of automatic bidding at *t*-1. The *Hour of Day* dummy variables are included but not reported.

**Significant at 5% level; ***Significant at 1% level. Robust standard errors are presented in parentheses.

TABLE 4 Fixed effect and expert imitation

	Count amount	Count bids	Degree amount	Degree bids	Balanced degree
	(1)	(2)	(3)	(4)	(5)
Lag Expert Amount Percent	0.121***	0.172***	0.137***	0.193***	0.166***
	(0.017)	(0.018)	(0.017)	(0.019)	(0.018)
Lag Total Bid Amount	0.145***	0.152***	0.145***	0.153***	0.145***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Lag Total Bids	0.004***	0.005***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag Percentage Needed (%)	0.001	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lag Percent Automatic Bidding	−0.547***	−0.541***	−0.536***	−0.556***	−0.554***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Lag Total Amount × Lag Percentage Needed (%)	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Bidders	1.267***	1.268***	1.269***	1.267***	1.267***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Obs.	432,882	432,882	432,882	432,882	432,882
R^2 (within)	0.709	0.709	0.709	0.709	0.709

Notes: This table shows the Fixed Effect Model results of the following: Count Amount Method, (2) Count Bids Method, (3) Degree Amount Method, (4) Degree Bids Method and (5) Balanced Degree Method. The dependent variable of all five clusters is *Log Hour Bid Amount*. *Lag Expert Amount Percent* represents the percentage of the total amount of the loan received from experts at time *t*-1. *Lag Total Bid Amount* shows the total amount of funding from collective investors at *t*-1. *Lag Total Bids* represents the total number of bids from lenders at *t*-1. *Lag Percentage Needed (%)* represents the percentage of the amount requested Zhang that is left unfunded at *t*-1. *Log Bidders* represents the logarithm of bidder numbers. *Lag Percent Automatic Bidding* shows the percentage of automatic bidding at *t*-1. The *Hour of Day* dummy variables are included but not reported.

***Significant at 1% level. Robust standard errors are presented in parentheses.

higher incomes, as high-income applicants can be considered less risky. *Debt-to-Income Ratio* takes a negative coefficient, suggesting that investors tend to avoid borrowers with high debt levels. *Credit Risky* has a negative coefficient in all five columns. To avoid risk, investors are certainly filling loan requests of applicants with better credit scores. *Maturity* takes a negative coefficient; investors on *Renrendai* seem to prefer short-term loans over loans that mature further into the future. The negative coefficient associated with the interaction between *Lag Total Bid Amount* and *Lag Percentage Needed* suggests that as a listing approaches completion, investors will reduce their funding to that particular list.[6] Given the speed of the action on Renrendai.com, investors must be quick in identifying opportunities for new listings are posted as the older ones fill over the course of the day. Overall, the findings in Table 3 provide evidence of expert imitation and herding, and the role of the remaining variables in the model is similar to results in earlier work.

[6]We observe a negative coefficient for the interaction term in Table 5, as well.

TABLE 5 Active versus new investors

	Active	New	Active experts	Active non-experts
	(1)	(2)	(3)	(4)
Hour Expert Amount Percent	0.108***	−0.002	−0.028*	0.193***
	(0.006)	(0.017)	(0.016)	(0.017)
Lag Total Bid Amount	0.337***	0.281***	0.323***	0.429***
	(0.013)	(0.011)	(0.015)	(0.016)
Lag Total Bids	0.011***	0.010***	0.010***	0.011***
	(0.002)	(0.001)	(0.002)	(0.002)
Lag Percentage Needed (%)	0.011***	0.014***	0.014***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)
Lag Percent Automatic Bidding	−0.764***	−0.531***	−0.613***	−0.687***
	(0.018)	(0.014)	(0.016)	(0.016)
Amount Requested	0.118***	0.050***	0.080***	0.022***
	(0.007)	(0.007)	(0.007)	(0.008)
Interest Rate (%)	0.015***	0.012***	0.019***	0.017***
	(0.000)	(0.001)	(0.001)	(0.001)
Maturity	−0.018***	−0.012***	−0.017***	−0.017***
	(0.000)	(0.000)	(0.000)	(0.000)
Credit Risky	−0.077***	−0.119***	−0.038***	−0.102***
	(0.008)	(0.009)	(0.009)	(0.011)
Debt-to-Income Ratio	0.016	0.019*	0.021*	0.029**
	(0.011)	(0.011)	(0.011)	(0.011)
Monthly Income	0.012***	0.007	0.011***	0.015***
	(0.003)	(0.004)	(0.004)	(0.005)
High Education	0.017***	0.001	0.022***	0.015**
	(0.006)	(0.007)	(0.007)	(0.008)
Log Bidders	1.271***	1.424***	1.371***	1.332***
	−0.003	(0.003)	(0.003)	−0.003
Lag Total Amount × Lag Percentage Needed (%)	−0.002***	−0.002***	−0.002***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	354,252	246,491	255,174	235,411
R^2	0.855	0.867	0.863	0.857

Notes: This table shows the OLS result with *Log Hour Bid Amount* as the dependent variable. The investor is defined as *Active* if she bid during the first 3 months of a 4-month rolling window. Otherwise, the investor is defined as *New* if she entered the window only in the 4th month. *Expert* is defined based on the balanced degree definition. *Lag Expert Amount Percent* represents the percentage of the total amount of the loan received from *Expert* at time *t*-1. *Lag Total Bid Amount* shows the total amount of funding from collective investors at *t*-1. *Lag Total Bids* represents the total number of bids at *t*-1. *Lag Percentage Needed (%)* represents the percentage of the amount requested that is unfunded at *t*-1. *Amount Requested* represents the requested loan amount. *Interest Rate (%)* represents the annual interest rate of the loan. *Maturity* represents the loan duration in months. *Monthly Income* represents the monthly income of the particular borrower. *High Education (1 = yes)* represents whether the borrower holds a high education certificate. *Credit Risky (1 = yes)* represents that the listing's credit grade is E, F or HR, else = 0. *Debt-to-Income Ratio* represents the ratio of the borrower's monthly debt divided by gross income before they apply for loans. *Log Bidders* represents the logarithm of bidder numbers. *Lag Percent Automatic Bidding* shows the percentage of automatic bidding at *t*-1. The *Hour of Day* dummy variables are included but not reported.

*Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Robust standard errors are presented in parentheses.

4.2 | Listing heterogeneity and payoff externalities

Having confirmed the sequential correlation for expert variation, we introduce listing fixed effects to control for listing heterogeneity. We include listing fixed effects to check for whether the expert imitation and herding are overestimated, as the positive sequential correlation result could be driven by the unobserved heterogeneity across listings and payoff externalities among lenders. Thus, all listing- and borrower-specific characteristics are dropped from our econometric specifications.

When we inspect Table 4, we find that *Lag Expert Amount Percent* still takes a highly significant positive coefficient, which suggests the presence of expert imitation on *Renrendai.com*. *Lag Total Bid Amount* is statistically significant and positive. This suggests herding behaviour in the community. These findings confirm that the expert, as well as the herding, exist in the P2P market. Furthermore, herding seems to be overestimated in the main result. *Lag Total Bids* has a positive effect on the investors' decisions, which is consistent with the earlier results (Zhang and Liu, 2012). The coefficient of *Log (number of) Bidders* is significantly positive, which suggests that the number of lenders on the market increases the amount that a listing receives. Finally, the interaction term *Lag Total Bid Amount* × *Lag Percentage Need* does not take a significant coefficient. Overall, the findings in Table 4 corroborate the expert imitation evidence and herding evidence in our main results.

4.3 | Extensions

Our analysis is further extended by the categorization of investors based on recent experience. Within every 4-month rolling window, we identify *Active Investor* if she invested during the first 3 months. However, an investor can enter the window in the 4th month; in this case, she is defined as *New Investor*. We split investors based on experience because the expert imitation comes from observational learning during the learning interval. Without sufficient learning, it is rarely possible to acquire expert acknowledge. Furthermore, although some *New Investors* might have participated in the previous windows, because "expert" is continually updated, the lack of earlier activity in a window indicates that they are less likely to observe and learn during the current rolling window. Active investors are further split into experts and non-experts based on the balanced degree definition of experts. Active investors are not always considered experts. Active non-experts have a level of investment that is lower in frequency and quantity as compared to those identified as experts. Hence, Model (1) is estimated for all four groups and the results are reported in Table 5.

When we examine the effect of expert imitation on active investors (Column 1), we find that *Active Investors* are likely to imitate the decisions attributed to experts. Meanwhile, the coefficient of *Lag Total Bid Amount* suggests that these *Active Investors* also herd. Interestingly, when we compare these results to *New Investors* (Column 2 of Table 5), we do not detect the expert imitation while herding is still present: The coefficient of *Lag Total Bid Amount* is positive and significant for this group suggesting that the new investors are inclined to follow the collective investors' decisions. This is perhaps because the new investors have not observed enough listings to identify experts and, thus, they prefer to simply follow the crowd.

When we examine the behaviour of both active experts and active non-experts as reported in Columns 3 and 4, we find that the latter are positively affected by other experts' decisions, while the evidence for the former is not conclusive (negative and weakly significant). This phenomenon can be explained by the difference in perception between both experts and non-experts. When they observe historical biddings, non-experts might be geared towards using information extracted from experts' bids as an aid to their investment decisions, whereas experts do not pay attention to other experts.

However, both types of investors are positively affected by the *Lag Total Bid Amount*, which suggests that both experts and non-experts herd, whereas non-experts are more likely to follow the crowd decisions.

5 | CONCLUSION

During the past decade, online peer-to-peer lending platforms have benefited both investors who sought better returns for their hard-earned savings and credit-constrained borrowers who had difficulty obtaining loans by resorting to traditional means. However, P2P lending platforms are still in development; in particular, most investors are not adequately equipped with the expert knowledge to cope with the risks associated with lending on these platforms. Earlier literature has shown that, under uncertainty, investors herd. However, given that investors can observe historical data about the lending behaviour of all other investors, it would be possible to single out investors who have expert information on listings posted on the platform. When such individuals are identified through observation, rather than blindly following the crowd, that is, herd, investors may prefer to follow expert behaviour and mimic their lending pattern.

Our research focuses on data extracted from *Renrendai.com* and shows, for the first time that observational learning takes place in P2P markets and that naïve investors learn through observation and imitate market leaders' lending behaviour. Using sequences of rolling windows over historical bidding data, we empirically identify some investors as experts using count methods and network centrality measures. Although these measures are different from each other, they successfully capture the top investors in the P2P community and provide similar results. Introducing these measures into an empirical framework similar to models that researchers have used to examine the presence of herding behaviour, we show that experts' lending behaviour significantly and positively affects the lending behaviour of the remaining P2P investors in the community. In other words, we provide evidence that investors observe and learn from experts and act in line with expert behaviour.

Finally, we show that experts do not follow other experts in the community, but they have the tendency to herd. This is perhaps because herding behaviour is ultimately subconsciously inherent in all living beings. We believe that further research along these lines would be beneficial.

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